Safe Learning for Near-Optimal Scheduling

QEST'21

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Scheduling hard and soft tasks

- Task system: Set of tasks partitioned into hard and soft tasks H and F.
- Each task generates instances called jobs.
- Tasks are preemptible: the scheduler can stall one job, and continue another job

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Tasks are tuples (C, D, A) such that

- $D \in \mathbb{N}$ is the (relative) deadline of all jobs generated by the task
- $C : \{1, 2, \ldots, D\} \to [0, 1]$ is a discrete probability distribution over possible job-computation times,
- $A : \{D, D + 1, \ldots\} \to [0, 1]$ is a distribution over finitely many possible inter-arrival times.

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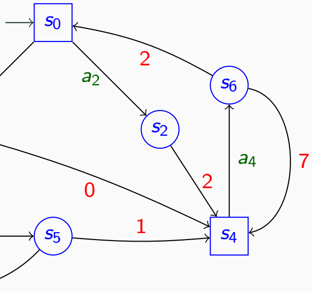
- Hard tasks should never miss a deadline
- soft tasks have an associated cost $c \in \mathbb{Q}, c \geq 0$.

Markov decision process

We model a task system as a Markov decision processes.



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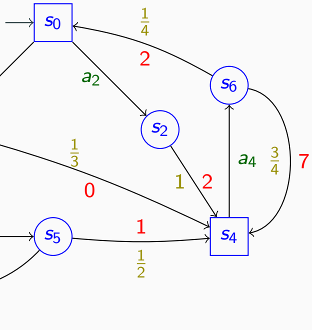

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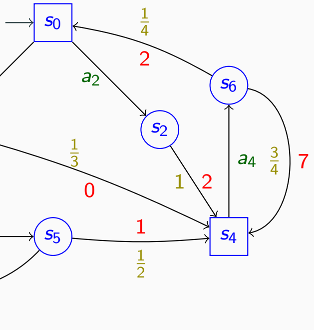

- Play in the MDP: s_0 Total cost: 0

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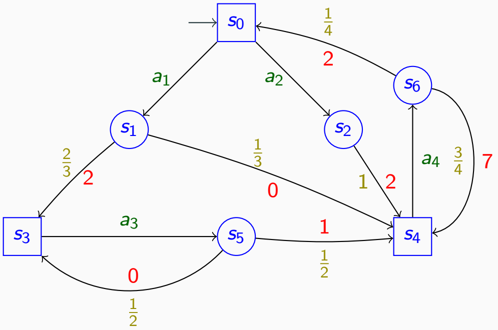

- Play in the MDP: $s_0 \xrightarrow{a_1} s_1 \xrightarrow{2} s_3$ Total cost: 2

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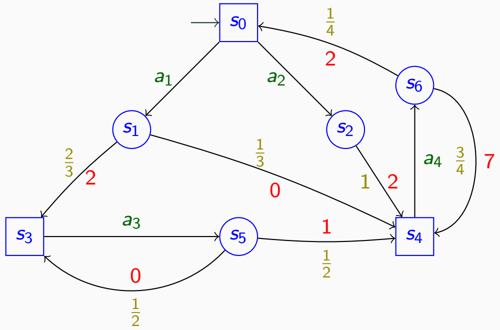

- Play in the MDP: $s_0 \xrightarrow{a_1} s_1 \xrightarrow{2} s_3 \xrightarrow{a_3} s_5 \xrightarrow{1} s_4$ Total cost: 3

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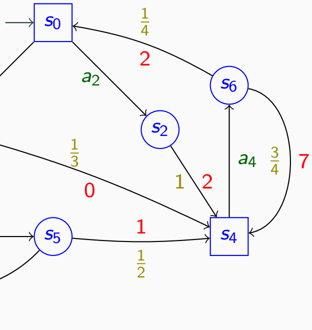

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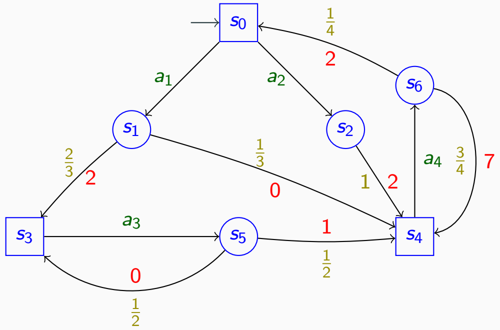

- Play in the MDP: $s_0 \xrightarrow{a_1} s_1 \xrightarrow{2} s_3 \xrightarrow{a_3} s_5 \xrightarrow{1} s_4 \ldots$ Total cost: 3
- Mean cost: $\lim_{n \to \infty} \frac{1}{n} \sum_{i=0}^{n-1} cost_i$, where $cost_i$ is the cost at i^{th} step

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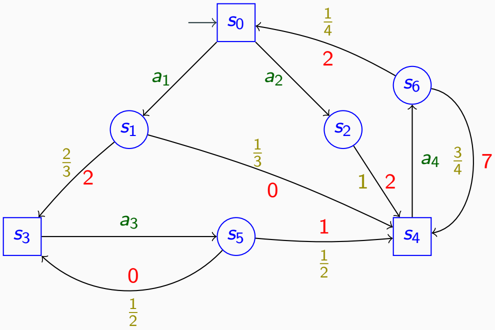

- Strategy $\sigma : Path_\Box \to Actions$

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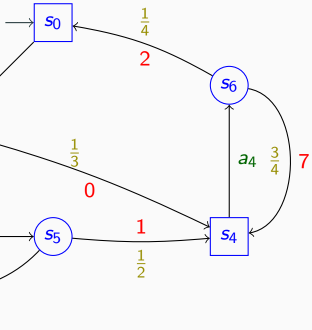

- Strategy $\sigma : Path_{\square} \to Actions$ creates a Markov chain $\Gamma[\sigma]$

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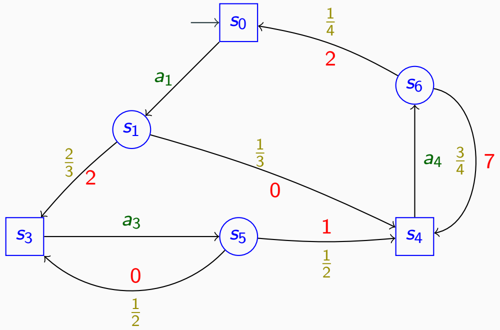

- Strategy $\sigma : Path_{\square} \to Actions$ creates a Markov chain $\Gamma[\sigma]$
- Expected mean cost of strategy σ: $\mathbb{E}\left[MeanCost_{\sigma}\right]$

MDP for scheduling problem

Consider the following task system with two tasks:

Task type	C	D	A	Cost
Hard	1	2	3	*n/a*
Soft	$[1 : 0.4, 2 : 0.6]$	2	3	10

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States

The states of the MDP contain the following information for each tasks:

- the remaining time $\hat{D} \leq D$ to deadline,
- a distribution $\hat{C} : \{1, 2, \ldots, \hat{D}\} \rightarrow [0, 1]$ over the possible remaining computation times,
- a distribution $\hat{A} : \{\hat{D}, \hat{D} + 1, \ldots\} \rightarrow [0, 1]$ over the possible times before next arrival of a job of that task.

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The initial state :

	$\hat{C}$	$\hat{D}$	$\hat{A}$
H	1	2	3
S	[1:.4,2:.6]	2	3

MDP for scheduling problem

Actions

The action of the MDP:
For Scheduler $\square$:

- Either chooses an active task and gives it one CPU time unit for execution,
- Stays idle (ε)

For Task Generator $\bigcirc$:

- Stays idle (ε),
- Finish the current job (*fin*),
- Submit a new job (*sub*),
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We update the next states accordingly.

MDP for scheduling problem

$\longrightarrow$

	$\hat{C}$	$\hat{D}$	$\hat{A}$
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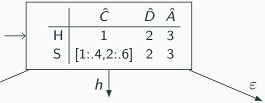

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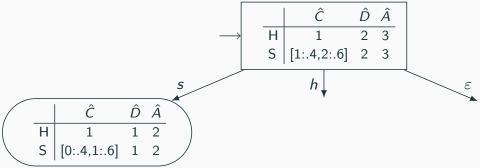

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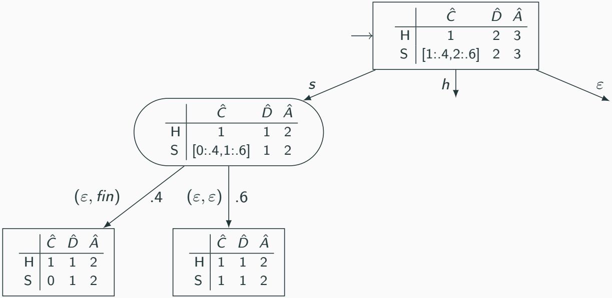

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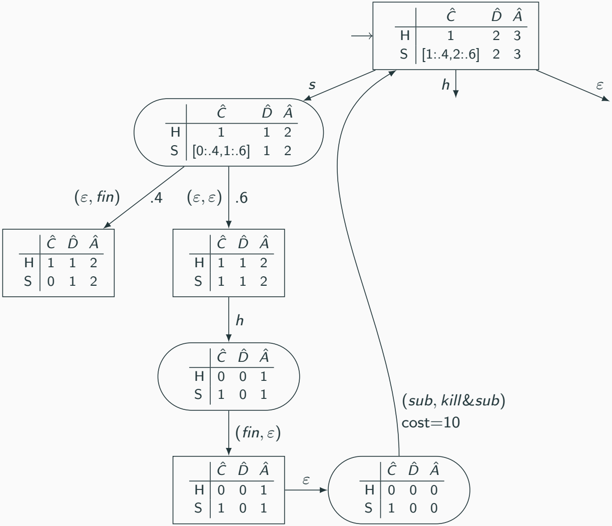

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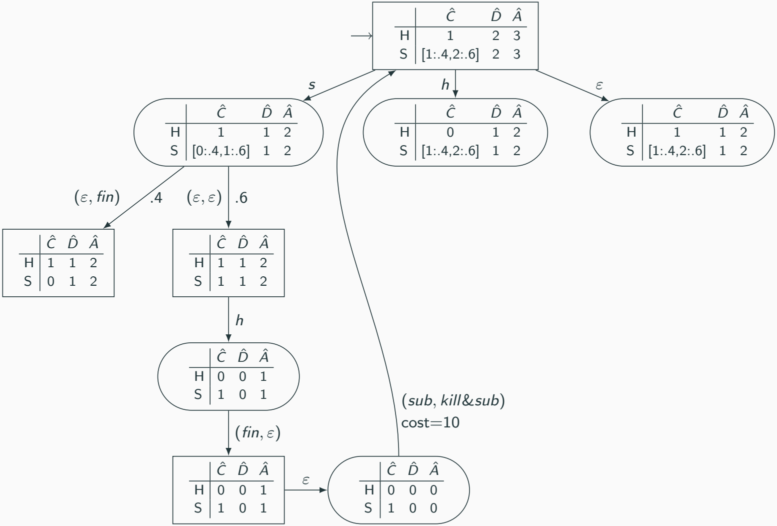

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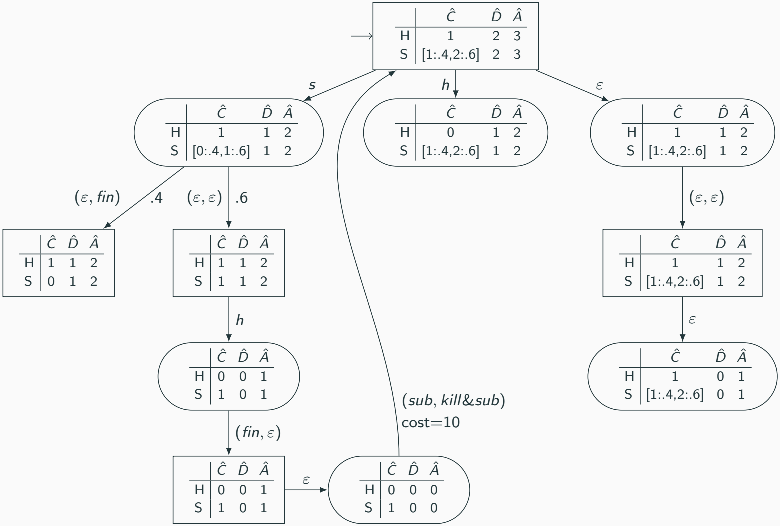

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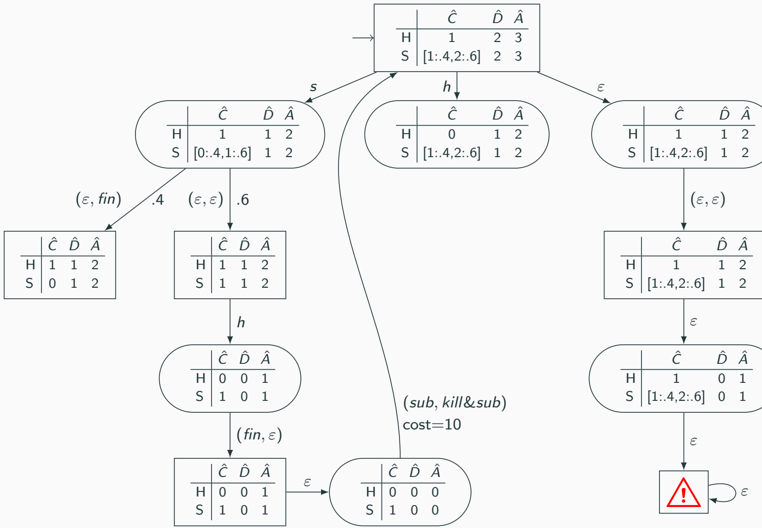

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Find a stratgy for scheduler that

- avoids the state ⚠ (denoted some hard task missing deadline),
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- Prune the MDP to obtain safe region: from all vertices scheduler has a strategy ensuring to visit only safe vertices
  - Polynomial time algorithm in the size of the MDP
- Find the strategy that minimizes the expected mean-cost in the safe region
  - Value iteration (Storm)

Model-based learning

Our settings

- Deadlines and the domains of the distributions are known
- Execution and inter-arrival time distributions are not known
- Need to sample to get "ϵ-close" distributions

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$p \sim^{\epsilon} q$ means $\forall a, \mid p(a) - q(a) \mid \leq \epsilon$

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Guarantees about learning

- Probably approximately correct (PAC): for all $\epsilon, \gamma \in (0, 1)$, can compute an ϵ-close task system, with probability $\geq 1 - \gamma$.
- safely PAC learnable: PAC learnable, and can ensure safety for the hard tasks while computing the approximation.
- (safely) efficiently PAC learnable : (safely) PAC learnable, and can compute the approximation in $PTIME$(size of the task system, $\frac{1}{\epsilon}$, $\frac{1}{\gamma}$)

Model-based learning

How would we learn an unknown distribution p?

- Collect samples according to the distribution p
- Calculate the relative frequency:
  $$r(a) = \frac{\text{number of times } a \text{ is sampled}}{\text{total number of samples}}$$
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:) Efficiently PAC-learnable

Model-based learning

Learning a task system with no hard tasks

for all tasks, repeat:

- Schedule the task when a job of this task is active till we collect enough samples of inter-arrival and computation time.
- Approximate the inter-arrival time and computation time distribution.

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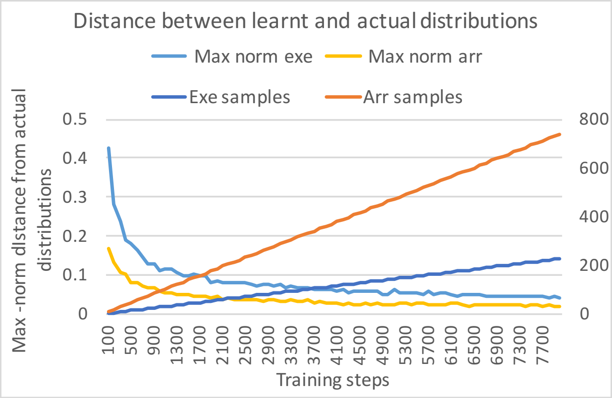

Learning distributions for a system with 6 soft tasks.

Model-based learning

Learning a task system with hard tasks

- :(Have to follow a safe scheduling strategy to learn safely
- :(May not observe enough samples if we follow a safe strategy
- :(Need a stronger condition on the task system

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Condition: good for sampling

For all soft tasks i, the safe region contains a state v_i where

- a new job of task i enters the system
- there exists a strategy σ_i that safely schedules the hard tasks and under σ_i, this new job is guaranteed to finish before deadline.

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- :) Safely PAC-learnable
- :(We cannot bound the time needed to get the next sample by a polynomial
- :(Not efficiently PAC-learnable

Learning a task system with hard tasks

More restrictive condition: good for efficient sampling

For all soft tasks, there is a set of scheduler vertices $Safe_i$ in the safe region such that

- from $Safe_i$, there is a strategy, under which all hard tasks and the task i can be safely scheduled
- there is a safe strategy σ_i for the hard tasks such that from any state in the safe region, $Safe_i$ is reachable within $K \in \mathbb{N}$ (polynomial in size of the task system) steps using σ_i.

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:) Safely and efficiently PAC-learnable

Example

Consider the following task system:

Task id	Task type	C	D	A	Cost
1	Hard	1	2	4	n/a
2	Soft	$[1 : ?, 2 : ?]$	2	3	10

We do not have a safe schedule that can ensure the soft task never misses a deadline.

- $Safe_2 = \phi$
- 'Good for efficient sampling' condition does not hold

But at time $12n + 6$, $n \geq 0$:

- a new job by the soft task enters the system
- this new job can be scheduled and guaranteed to finish under a safe strategy
- 'Good for sampling' condition holds

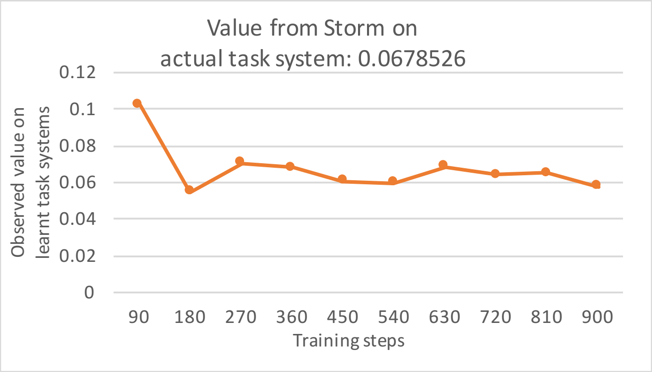
Model-based learning

Using the learnt model

Given a task system Υ, $\beta, \gamma \in (0, 1)$:

- Calculate appropriate ϵ
- Learn a system Υ^M, which is ϵ-close to Υ with probability $\geq 1 - \gamma$
- Compute optimal safe scheduling strategy σ in the MDP corresponding to Υ^M

- σ is a safe strategy in Υ
- With probability $\geq 1 - \gamma$, in Υ, $|\mathbb{E}\left[MeanCost_\sigma\right] - \min_\tau \mathbb{E}\left[MeanCost_\tau\right]| \leq \beta$



Model-based learning for 1 hard, 2 soft tasks

Model-free learning

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Receding horizon framework

* Fix a horizon H
* At each step, find the best action based on a unfolding tree of depth H
* Use heuristic algorithms like Monte-carlo tree seach
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Deep Q-learning

- Use discount factor close to 1
- Use shielding to restrict actions during learning process so that only safe actions can be used

Model-free learning

Strategies used for advice in MCTS and shielding in deep Q-learning

Earliest deadline first

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- Allow all safe edges from a scheduler vertex

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Most general safe scheduler

- Allow all safe edges from a scheduler vertex

:) allows for maximal exploration

:(need to be precomputed (AbsSynth)

Experimental results

Task	MDP size	STORM output	MCTS unsafe	MCTS MGS	MCTS EDF	Deep-Q unsafe	Deep-Q MGS	Deep-Q EDF
4S	10^5	0.38	0.52	NA	NA	0.56	NA	NA
5S	10^6	TimeOut	0	NA	NA	0.13	NA	NA
10S	10^{18}	TimeOut	0	NA	NA	0.96	NA	NA
1H, 2S	10^4	0.07	0.67	0.14	0.28	0.24	0.11	0.22
1H, 3S	10^5	0.28	1.13	0.45	0.49	∞	0.47	0.47
2H, 1S	10^4	0	0.92	0	0.2	∞	0.02	0.3
2H, 5S	10^{10}	TimeOut	3.44	1.93	2.14	∞	2.39	2.48
3H, 6S	10^{14}	TimeOut	4.17	2.88	2.97	∞	3.42	3.47
2H, 10S	10^{22}	TimeOut	0.3	0.03	0.03	∞	1.42	1.6
4H, 12S	10^{30}	TimeOut	2.1	1.2	1.3	∞	2.68	2.87

Comparison of MCTS and reinforcement learning.[1] [2]

[1] ∞ refers to task systems missing deadline for hard tasks

[2] The values reported for both MCTS and Q-learning are obtained as an average cost over 600 steps.

Thank You!